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Research Article

Application of MNDWI index for flood damage area calculation in Lam river basin using google earth engine platform

Ngoc Minh Trinh[1*]

[1] Faculty of Hydrology, Meteorology and Oceanography, Vietnam National University - Hanoi University of Science; trinhminhngoc@hus.edu.vn

*Corresponding author: trinhminhngoc@hus.edu.vn; Tel.: +84–966610784

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Abstract: Floods, as natural occurrences, often result in significant impacts on human life. The construction of flood maps plays a crucial role in devising appropriate strategies to mitigate the adverse effects of floods. In recent decades, there has been notable attention towards flood mapping methods utilizing remote sensing images. This paper introduces a methodology for generating an inundation map for rainy season and river network. To achieve this objective, we investigated the use of the recently developed Modified Normalized Difference Water Index (MNDWI) within the Google Earth Engine platform for extracting surface water. The study yielded flood maps extracted with considerable precision, facilitating the calculation and analysis of flood extents within the study area.

Keywords: Flood damage; Sentinel–2; Google earth engine.

1. Introduction

Since the dawn of history, floods have been one of the natural disasters that have appeared and caused a tremendous influence on human life. Especially in recent decades, floods have become increasingly fierce and unpredictable. Statistics show that the number of people affected by floods increased steadily from 147 million people per year (1981-1990) to 211 million people per year (1991-2000) [1]. Countries that have suffered from the severity of floods include China (2007), Thailand (2011), Japan (2011), India (2012), Myanmar (2012); in Europe: Central and Eastern European countries (2006 and 2013), France, Greece, Turkey (2007); in the Americas: Guatemala (2005), the United States (2009); in Africa: Angola (2010), Nigeria (2010) [2, 3]. Accordingly, it may be considered that floods are global in nature and increasingly complex, causing heavy damage. In terms of scale, they are not as intense as a tsunami or storm, but their impact is long-lasting and leaves many atrocious consequences for future generations.

Vietnam has faced floods since ancient times. This disaster occurs widely across the country, with floods appearing most frequently in the Central region, where rivers have steep slopes and high water concentration. In the Central region, the flood time is very rapid due to the swift flow of rivers and the inappropriate management of irrigation and hydroelectric reservoirs. As a result, the occurrence of floods, both natural and artificial, is quite frequent, posing significant challenges and obstacles for flood prevention management [4]. Flood situations and damage in some river basins in the Central region, such as the Lam River basin (total damage due to storms and floods in the 21 years from 1990 to 2010 amounted to more than 3,300 billion VND), Vu Gia - Thu Bon (from 1997 to 2009, natural disasters in the Vu Gia - Thu Bon river basin resulted in 765 deaths, 63 missing persons, and 2,403 injuries, with a total property damage value of more than 18,000 billion VND), and Ve - Tra Khuc (from

1996 to 2010, natural disasters caused 601 deaths and missing persons, 1,017 injuries, and the collapse and sweeping away of 8,501 houses [5–7]. According to statistics from 1990 to 2010, the Ca River basin suffered 34 direct landfall storms, with an average of 1 to 1.5 storms each year. The wind speed caused by the storms reached level 9 to 10, with gusts up to level 12. Storms often arrive in the Ca River basin from late September to early November. The maximum wind speed observed in Tuong Duong was 25 m/s in the west-north direction (1975), in Quy Chau, it exceeded 20 m/s in the west-north direction in 1973, and in Do Luong, it reached 28 m/s in the east-north direction (1965). Regarding floods, in the past 21 years, there have been 29 significant floods causing tremendous damage to people and property. Floodwater level monitoring data over the past 40 years shows that the greatest floods occurred in the main stream. Notable floods in the Ca River basin include those in 1954, 1963, 1973, 1978, 1988, 2007, and 2010. On average, major floods occur every 9 to 10 years. Some years have resulted in dike failures, as seen in the floods of 1954, 1978, 1988, and 1996. Especially in the flood of 1954, many dikes were breached (from Nam Dan to the sea), with floodwater flowing from the river into the fields for a continuous 16-days period. The total damage caused by storms and floods in the 21 years from 1990 to 2010 amounted to more than 3,300 billion VND. Solutions to minimize damage caused by floods include a set of structural measures (building flood prevention works, diverting floods, and relocating structures and people from flood-prone areas) as well as non-structural solutions [8–10]. The group of construction solutions is often directly effective but requires significant funds, making some solutions in this category challenging to implement. Therefore, priority is given to solutions within the non-structural group. One effective non-structural solution involves establishing a database with information on floods, risks, and the potential impact of floods on people's economic livelihoods. This includes data on flood depth, the extent of flooded areas within the city, and flood-prone zones [11–13]. Creating such a database enables localities to proactively formulate timely plans and solutions when faced with floods, representing a reasonable choice with high economic efficiency. In recent years, flood maps have become an increasingly effective tool for assessing the impact of floods on people. These maps provide a visual representation of the scope and level of flooding. Currently, there are various methods for constructing flood maps, with the most popular one recently applied in Vietnam being a combination of hydraulic modeling and GIS tools. This method has been implemented for more than a decade, utilizing both one-dimensional and two-dimensional models to construct flood maps. Notable applications include the study [14, 15] for the Quang Nam, the study [16, 17] for rivers in Khanh Hoa province, and [18, 19] for the Ben Hai and Thach Han river systems. While this method yields positive results and offers flexibility in calculating scenarios, it does have several limitations. A significant requirement is the considerable amount of input data needed for the model, necessitating time and effort for field surveys, data collection, and editing. The utilization of this method requires an experienced expert to verify and calibrate the model appropriately. Notably, in areas affected by rainfall in the field, the current hydraulic model may not fully address the issue. However, with the advancement of remote sensing technology, a new avenue has emerged for data collection and analysis. Remote sensing images have the capability to collect data over a broad area and an extended period with high repetition frequency. The availability of free satellite sources enhances the potential of this method as a valuable resource The method of using remote sensing images has been adopted by numerous domestic and international authors to determine the extent of flooding. The study [20] determined the coastline by calculating the difference threshold between the reflection levels in the green band and the NIR and MIR bands. However, the use of optical images may be hindered if the sky is covered with clouds, especially during periods of heavy rain. This challenge was addressed by [21–23] who utilized remote sensing images, ensuring that the information received is not limited by cloud cover. While this approach is suitable, it does not distinguish between various water bodies (such as rivers and lakes) and flooded lands. Additionally, the study compared the differences between flooded and unflooded photos to discern areas affected by rain and areas with regular water presence.

This article presents the results of creating flood maps for the Lam River using Multiband Water index (MNDWI), implemented on the Google Earth Engine cloud computing platform. Google Earth Engine is a cloud-based geospatial analysis platform that enables users to visualize and analyze Earth satellite imagery. The platform's dataset encompasses over 40 years of historical and current global satellite imagery, along with the tools and computing power necessary to analyze and mine that extensive data trove without the need to download it to a local computer. Additionally, for more specific research purposes, users can create custom scripts by visiting https://code.earthengine.google.com/ [25,26]. From the perspective of flood research, the study [24] highlighted that with GEE, users no longer need to switch between different platforms where data is originally collected and distributed, so that GEE applications are reusable and can work with many different configurations. In the Field of Flood Research, it further demonstrates its usefulness by improving the reusability of GEE scripts and creating ready-to-use applications for other research areas, thus making it possible quickly create a flash flood map.

2. Materials and methods

2.1. Description of the study area

The Lam River basin, the second largest in the North Central region, originates from the mountainous areas of Laos. Covering an expansive area of 27,200 square kilometers within Vietnamese territory, it stretches from 18°15' to 20°10'30" North latitude and 103°45'20" to 105°15'20" East longitude. This basin encompasses significant portions of Nghe An and Ha Tinh provinces, along with a part of Nhu Xuan district in Thanh Hoa province.

The primary stream of the Lam River originates from the lofty peaks of Xieng Khouang province in Laos, where it gains elevation of over 2,000 meters. Initially flowing in a Northwest - Southeast direction, it then veers to a West - East trajectory before eventually meeting the sea at Cua Hoi. Despite its considerable length of 531 kilometers, the Lam River maintains a relatively stable main bed with minimal mudflats, showcasing a meandering coefficient of 1.74. With a river density of 0.6 km/km^2, the Lam River system is bolstered by 44 level I tributaries, which contribute significantly to its hydrological dynamics. Noteworthy among these tributaries are the Nam Mo River, Hieu River, Giang River, and La River. These tributaries, often originating from regions characterized by heavy rainfall, have a significant impact on the overall flow patterns within the basin [7, 27].

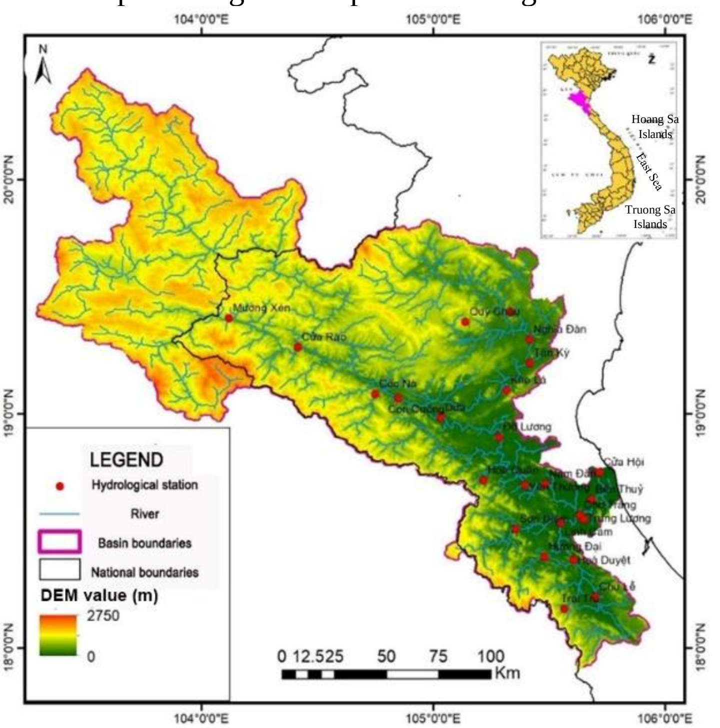

Figure 1. Map of the study area - Lam river basin.

One of the most pressing challenges facing the Lam River basin is the occurrence of significant floods, primarily attributed to prolonged heavy rainfall on a large scale, coupled with the basin's slope and intricate river network. These floods, concentrated predominantly in the middle and lower reaches of the basin, are characterized by total rainfall exceeding 650 mm in the rain center, with extreme events reaching up to 1,500 mm, as witnessed during the devastating flood of 1978. An intriguing aspect of floods in the Lam River basin is the occurrence of dual peaks, particularly notable in major flood events such as those in 1978, 1988, 1980, and 2008 [28, 29]. The latter peak tends to be larger than the initial one, accentuating the complexity of flood dynamics within the basin. Notably, these peaks often coincide with the saturation of the basin's storage capacity, typically observed during the month of September. Understanding the intricate characteristics of the Lam River basin is paramount for effective flood management and mitigation strategies. By comprehensively analyzing its hydrological patterns, tributary dynamics, and flood behavior, policymakers and stakeholders can implement targeted measures to minimize the impact of floods and safeguard the communities residing within the basin and its vicinity.

2.2. Methods

While numerous techniques for extracting surface water have been introduced in previous studies, accurately extracting surface water in areas with low-reflectance background surfaces, such as mountainous shadows, high building shadows, and dark built-up areas like asphalt roads and dark building materials in downtown, remains a challenging problem. The presence of low-reflectance surfaces can lead to misclassification due to their similar low reflectance with surface water [25, 30, 31].

The passage discusses the development of a Modified Normalized Difference Water Index (MNDWI) aimed at improving the accuracy of surface water extraction in regions with complex backgrounds. The study evaluates the effectiveness of the proposed MNDWI compared to six other commonly used water indices across various climatic zones and seasons. The objective is to create a water index (MNDWI) that consistently delivers highly accurate surface water extraction, even in the presence of environmental noise.

In Vietnam, there are various approaches for calculating the MNDWI index on Landsat images, used for studying water resource changes [32], assessing coastline changes [33], and urban surface water body changes [34]. These studies typically involve downloading satellite images and processing them using specialized software, which can be limited due to pre- and post-processing requirements and the computational demands of the software. However, using platforms like Google Earth Engine (GEE) can overcome these limitations by providing efficient processing and reducing solution time [24, 30].

The study [35] specifically focuses on calculating three water indices (NDWI, MNDWI, and WNDW) to interpret water areas in Sentinel–2 images on the GEE platform. The results show high efficiency in processing and solution time, indicating the potential of using GEE for remote sensing image analysis, particularly for water resource monitoring and management in Vietnam.

The MNDWI was chosen for water classification, since it has produced the best results in the literature among the index-based algorithms. The MNDWI is based on distinctions between water and other low-reflectance surfaces [36], restricting the brightness value ranges used to those in the lower or "darker" section of the terrestrial spectral range, being characteristic of water [37]. The MNDWI is intended to limit non-water pixels while improving surface water information. The study [38, 39] provided details of the concept of MNDWI, and the calculation is given in Equation (1). In addition, to eliminate mountainous shadows that were mistakenly classified as water bodies, we placed a threshold of 5% slope over the study area, and areas with higher slopes were automatically excluded from the water class.

$$\text{MNDWI} = \frac{\text{Green} - \text{SWIR}}{\text{Green} + \text{SWIR}} \quad [40–42] \tag{1}$$

where Green is the pixel values from the green band; SWIR is the pixel values from the short-wave infrared band.

The research methodology is depicted through the following research diagram (Figure 2).

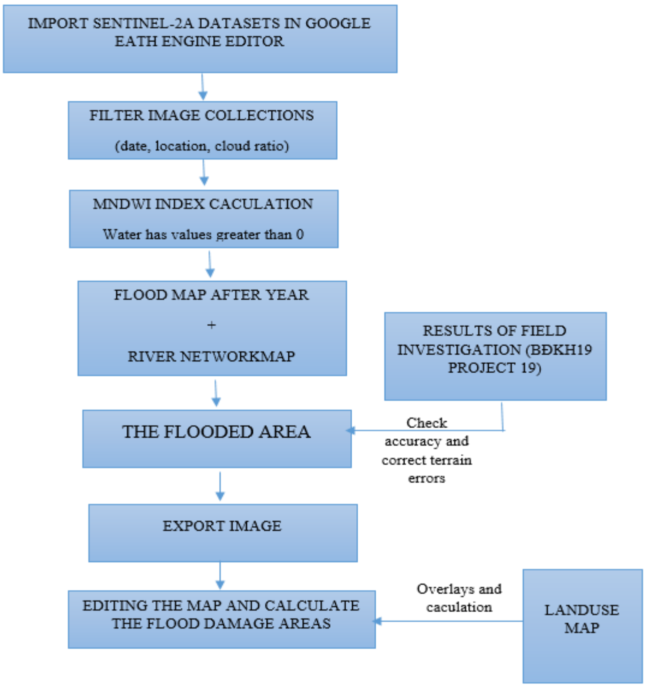

Figure 2. Flowchart illustrating the research steps.

2.3. Data collection

The authors utilized Sentinel–2 remote sensing imagery with a spatial resolution of 10 meters from the Google Earth Engine dataset. The dataset comprises 178 images acquired between October 1, 2015, and October 31, 2022, which were employed to construct a comprehensive river and stream network map. Specifically, an image captured on October 17, 2022, was employed to generate a flood map post-rainfall. By overlaying these two maps, the flood extent was extracted (Figure 3). Given that each individual image only covers half of the basin area, the authors undertook specialized processing of image pairs to seamlessly combine them, thereby creating a unified image of the entire basin. Figure 2 illustrates the process flowchart for distinguishing and identifying flooded and non-flooded areas using the Modified Normalized Difference Water Index (MNDWI) on the Google Earth Engine (GEE) platform as implemented in the study. The steps and main processes for Sentinel–2 image interpretation can be summarized as follows. Firstly, Sentinel–2 images covering the study area are collected. Next, image processing is conducted to eliminate the effects of noise factors. Subsequently, a high-pass filter is applied to homogenize the spatial resolution (10 m) for all bands. Using the MNDWI index, pixels are classified into water and non-water (post-rain flood) areas within the study area. Finally, the computed results are evaluated to assess the accuracy of identifying, distinguishing, and interpreting water and non-water areas within the study region. Post-rain flood areas and river/stream networks are overlaid to calculate the flooded areas. Then, these areas are extracted in vector form and inputted into MapInfo software for comparison with land use maps, calculating damage extents for each land type, and editing the final product map.

The test data includes the flood map of the Lam River basin developed as part of the BDKH19 project in 2015, along with flood trace survey data from 2013 to 2014 [40, 41], as documented in previous studies [7, 9, 28]. These datasets were utilized to perform a comparative analysis with the threshold classification results. The comparison revealed that the flood area calculated using both methods exhibited equivalent accuracy, reaching 99%.

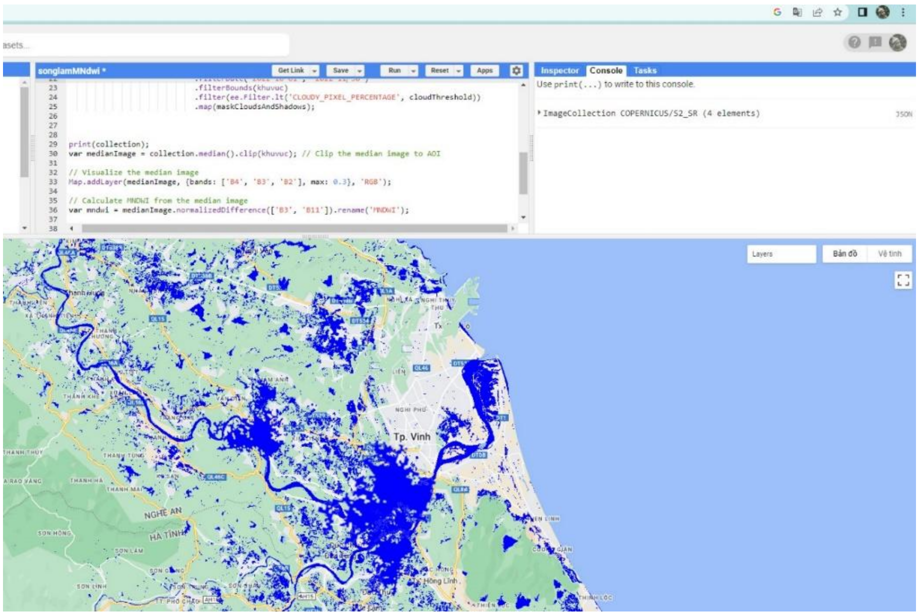

Figure 3. The output of water mask interpretation (MDNWI menthod) in Google Earth Engine.

To assess the accuracy of interpretation results derived from remote sensing imagery, the study incorporated additional field datasets comprising flood trace surveys (comprising 200 surveys) using the Kappa error construction method [42–44]. The Kappa error of the interpretation results obtained from remote sensing imagery demonstrated a high accuracy level, reaching 97%.

3. Results and discussion

The analysis of satellite images (Figure 4) revealed that the total flooded area spans 98,143 hectares. Predominantly, flooding is concentrated in several districts, including Ky Son and Tuong Duong (Nam Mo - Nam Non river area), Que Phong and Quy Chau (Upper Hieu river), Quy Hop Nghia Dan, Thai Hoa, Tan Ky, and Con Cuong (Ca river), as well as Anh Son, Do Luong, Thanh Chuong (Ca river), parts of Huong Son, Huong Khe, Vu Quang, Duc Tho (Ngan Pho, Ngan Sau, La rivers), and Hung Nguyen, Nghi Loc (Lam River downstream) districts. The areas affected by flooding mainly concentrate in the downstream areas of Thanh Chương, Nam Đàn, Đàm Đàn, and Hưng Nguyên districts. Places less affected by floods are typically mountainous regions, primarily consisting of forested and perennial crop lands. This result is consistent with the findings in document [4] when calculating flood exposure. The obtained results closely resemble those of previous flood studies [4, 39, 40] utilizing flood models.

To assess the impact of flooding on land use categories within the study area, the authors utilized land use maps provided by the Ministry of Natural Resources and Environment in 2010, which delineate over 70 distinct land types. These were classified and grouped into five main categories: bare land and rivers, forest land and industrial crops, agricultural land and aquaculture, residential and commercial land, and public infrastructure. The results, as presented in Table 1, indicate that the scope of flood damage predominantly affects public infrastructure such as schools, hospitals, flood-resistant housing, administrative areas, and roads. The results indicate that areas used for public facilities such as schools, hospitals, storm shelters, administrative centers, and transportation routes are frequently prone to flooding. These locations often host large populations seeking refuge from floods and serve as centers for relief efforts. If transportation routes and densely populated areas are flooded, residents may become isolated, leading to increased risks to both lives and finances.

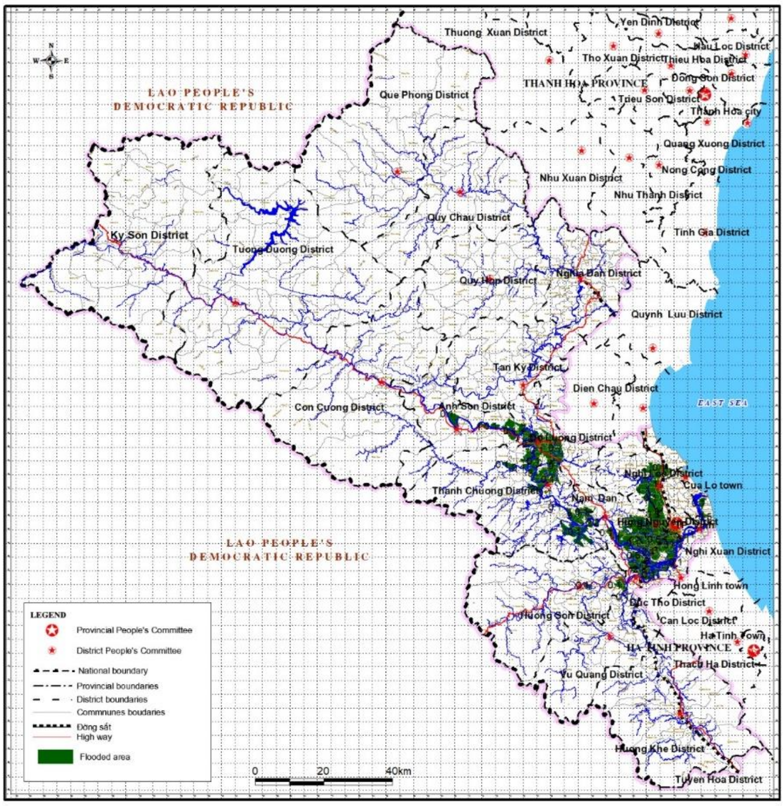

Figure 4. The Lam River basin flood map derived from remote sensing imagery, following the extraction of flood areas using Google Earth Engine.

Therefore, the government needs to inspect and maintain communication systems before the flood season to ensure the continuity of communication networks within flood-affected areas. Public infrastructure should be robust and spacious enough to accommodate residents seeking refuge. Residential and commercial land use areas are less susceptible to flooding compared to public infrastructure; however, since households' residences contain family assets including food supplies, livestock, and other household items, the government should encourage people to build homes in safe areas. Families at risk of flooding should be supported to construct sturdy residences meeting flood-resistant standards to mitigate flood risks.

Table 1. The range of damage due to flooding calculated through satellite image analysis results.

No	Land-use type	Damaged area (ha)	Damaged percentage (%)
1	Public land	45460	45.75
2	Housing land and production and business land	18255	18.37
3	Agricultural land and aquaculture land	14200	14.29
4	Forest land and industrial crops	16500	16.61
5	Bare land and rivers	4947	4.98
	Total damage	**98143**	**99362**

The residents living in the downstream area of the Lam River primarily engage in agriculture, with rice cultivation being the main source of food and income for them. When rice paddies and flower fields are flooded, it causes significant damage and long-term impacts on the livelihoods of the people. They have to wait until the next planting season to restore their production activities. However, rice and flowers are less resilient to flooding compared to other industrial crops, thus the extent of damage to rice paddies and flower fields during floods is higher than that of industrial crops. Meanwhile, vacant lands or higher ground near rivers are less prone to flooding.

4. Conclusions

The study has demonstrated the effectiveness of flood analysis results obtained from Sentinel–2 remote sensing images using the MNDWI method, yielding relatively good outcomes. The analysis revealed concentrated flooding in several districts, including Ky Son, Tuong Duong, Que Phong, Quy Chau, Quy Hop, Nghia Dan, Thai Hoa, Tan Ky, Con Cuong, Anh Son, Do Luong, Thanh Chuong, Huong Son, Huong Khe, Vu Quang, Duc Tho, Hung Nguyen, and Nghi Loc, with the Lam River downstream experiencing significant impact. Additionally, the study calculated the extent of flood damage, highlighting the predominance of affected areas in public lands (44.26%), agricultural lands (34%), and residential lands (22%), emphasizing their critical role in flood prevention efforts. The research findings contribute to flood damage assessment and monitoring, underscoring the need for local authorities to enhance flood prevention measures through robust planning and prompt implementation to restore normalcy in production and daily activities, thereby minimizing economic and human losses. Researching flood damage through inundation area using a remote sensing index remains constrained. In forthcoming studies, the author intends to expand their research by assessing the effects of water extraction through multiple remote sensing indices.

Author contribution statement: Conceived and designed the experiments; Analyzed and interpreted the data; manuscript editing: T.M.N.; Analysis tools or data; performed the experiments: T.M.N.; Wrote the draft manuscript: T.M.N.; Contributed reagents, materials: T.M.N.

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